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Joint adaptation framework in mobile ad hoc networks: A control theory perspective

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ABSTRACT

To enhance the performance of wireless communications in mobile ad hoc networks, existing methods focus on tuning one certain wireless variable such as rate adaptation, or two variables together such as joint power-rate adaptation. However, field tests reveal that not only the single controllable variable but also their correlation affect the performance. Tuning them one-by-one and ignoring their correlation cannot achieve the optima. In this paper, we study the adaptation problem from a distributed control perspective and present a general joint adaptation framework (JAF). Leveraging the multiple-input-multiple-out control model, JAF is scalable, which embraces all controllable variables as its inputs and target performance metrics as its outputs. Moreover, based on the closed-loop control theory, JAF adapts the optimal combination of variables through the feedback of the real-time measurements. Extensive simulations are conducted to evaluate the distributed JAF. As an example, every node using JAF jointly adapts its data rate and transmission power in our simulations. The simulation results demonstrate that JAF outperforms the existing methods by improving the throughput up to 13% and the packet delivery ratio up to 15% simultaneously.

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1. Introduction

A Mobile Ad hoc NETwork (MANET) [25] consists of multiple mobile nodes. Through equipped wireless devices, these nodes form a dynamic ad hoc network and share their data. MANETs are promising and have been widely adopted in various real world applications such as vehicular networks [11] and robotic networks [17]. With the support of MANETs, vehicles can avoid some crashes by safety message and industrial robots can collaboratively play the soccer.

Lots of wireless protocols can be used in MANETs. For example, vehicular networks utilize IEEE 802.11p based DSRC [1], robotic networks utilize 802.11g based WiFi, and wearable sensor networks utilize 802.15.4 based ZigBee. Although the protocols are different, these applications have the same need including high throughput and packet delivery ratio (PDR), to guarantee the quality of data sharing. In addition, the general wireless devices, even adopt different protocols, provide several controllable variables including transmission power, data rate, and etc.

In order to enhance the wireless performance in dynamic environment, many efforts have contributed on the adaptation methods. Most existing methods focus on tuning a single variable. For example, transmission power control [10], and data rate adaptation [21]. Some other methods consider the joint adaptation of two variables. For example, joint power-rate adaptation [14]. Nevertheless, field tests [1] reveal that every variable affects the performance. Hence, optimizing any one or two variables cannot achieve the optimal performance. In addition, existing adaptation methods cannot directly extend to multivariate adaptation well, because multiple variables have complex correlation and this correlation is dynamic in MANETs. The study on jointly adapting all wireless variables is still blank in the literature.

In this paper, we promote to study a general framework for multivariate adaptation in MANETs using a new perspective: distributed and adaptive control [7,12]. Two useful concepts are adopted. First, the *multiple-input-multiple-out* (MIMO) control model [16] is able to describe the complex correlation among all wireless variables as inputs and all performance of interests as outputs. Second, the closed-loop control system can update the dynamic correlation through the feedback of real-time performance,

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and thus the optimal control strategy can be decided according to the correlation. Based on these two concepts, we propose a novel *joint adaptation framework* (JAF), which adapts the optimal combination of multiple variables to enhance the performance. This general framework is also scalable for more controllable variables and performance in future MANETs.

Although the theoretical basis of JAF is the MIMO control model, the design of JAF is not a direct transplant of recent MIMO controllers. In order to enable JAF, it is necessary to address the particular challenges in MANETs. (i) The environment is highly dynamic. Hence, it is non-trivial to quickly capture the dynamic correlation of variables using recent MIMO controllers. (ii) Wireless communications in MANETs could adopt either broadcast or unicast transmission manners. In a hybrid broadcast/unicast scenario, it is difficult to measure the actual performance because there is no information feedback in broadcast manner.

To address these two challenges, we design two tailored techniques for JAF. First, for acquiring the correlation of multiple variables, a combined design of one offline trainer and one online trainer is proposed. The offline trainer provides an initial estimation of the coarse correlation and the online trainer accurately tracks the subtle change of dynamic correlation within a negligible duration. Second, to cope with the lack of coordination between mobile nodes, JAF utilizes the local measurements for approximating the performance of throughput and PDR. Based on the channel reciprocity, the core idea of local measurements is to exploit the receiver-side performance to estimate the transmission performance. The receiver-side performance can be locally measured and require no acknowledgements from neighboring nodes. This technique also allows JAF to operate in a fully distributed fashion.

Extensive simulations are conducted to evaluate JAF. A large amount of distributed nodes are moving, computing, and transmitting in a MANET. As an example, every node operating JAF jointly adapts its data rate and the transmission power. Compared with existing methods, JAF significantly improves the wireless performance, which increases the throughput up to 13% and the PDR up to 15% simultaneously.

The main contribution of this paper is two-fold.

- To the best of our knowledge, this is the first work to state the multivariate adaptation problem in MANETs. In addition, we resort to the control theory concept to study this problem.
- To enhance the wireless performance, we propose a novel and general JAF. Leveraging the modern control theory, JAF is not only scalable to all variables but also adaptive to the optimal performance. The design of JAF takes the highly dynamic nature and the hybrid communication manner into consideration.

The remainder of this paper is organized as follows. In Section 2, we state the problem. In Section 3, we build the basic model. We describe the design of JAF in Section 4, and analyze its features in Section 5. In Section 6, we evaluate JAF using extensive simulations. In Section 7, we review the related work. We conclude this paper in Section 8.

2. Problem statement

In this section, we present the system description and the problem statement.

2.1. System description

We describe the system using the model as depicted in Fig. 1. The wireless system is the basic component of this model, including the wireless radio device equipped on each mobile node and the wireless channel for data transmission. All the other factors connecting with the wireless systems are classified into three categories: outputs, inputs, and noises.

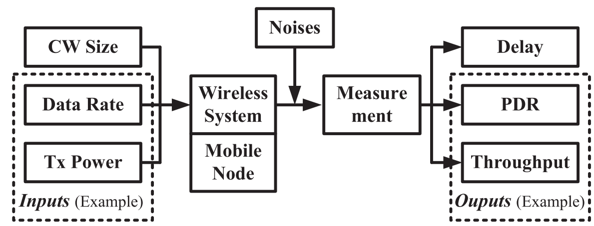

Fig. 1. The wireless system in MANETs has multiple inputs and outputs. As an example, we consider the inputs including the transmission power and the data rate, meanwhile the outputs including the throughput and the PDR.

• Outputs: The outputs are the performance of interests. Since the feasibility of most MANET applications relies on the efficient and reliable communications, we are interested in the performance on efficiency and reliability, which is characterized by two extended metrics, throughput and packet delivery ratio (PDR). Some other outputs may include delivery delay.

• Inputs: The inputs are the controllable variables in wireless devices. The transmission power and the data rate are common controllable variables offered by most wireless systems. Some other variables may include CW size and packet rate. It has been demonstrated that every variable significantly affects the performance [1,14,20]. In this work, we take the most common two variables into consideration.

First, the *transmission power* decides the transmission range, which indirectly impacts the throughput and the PDR. For example, the transmission power of DSRC is 0–30 dBm.

Second, the *data rate* is the number of bits transmitted per time unit. When the link quality is good, a high data rate can improve the throughput. When the link quality is poor, a low data rate is needed to guarantee the PDR. A wireless protocol provides several data rates. For example, there are eight alternative data rates in 802.11p based DSRC, which are {3, 4.5, 6, 9, 12, 18, 24, 27} Mbps.

• Noises: The noises are the uncontrolled variables in MANETs. These variables also affect the wireless performance, but they do not under control, such as SINR, velocity, and electrical characters of hardware. Furthermore, some noises cannot be directly measured, for example, the multi-path channel.

2.2. Multivariate adaptation problem

We propose the *multivariate adaptation* (m-Ada) problem, which aims to enhance the efficiency and the reliability of wireless communications in MANETs through jointly adapting all possible variables.

To address the m-Ada problem, the basic idea is to model the correlation between multiple inputs and outputs and then design the control strategy based on the correlation. There are two challenging issues in modeling the correlation:

(i) The correlation is complex. In MANETs, the relationship between inputs and outputs is not a simple one-to-one mapping. The correlation also exists among multiple inputs. For example, when the power is increased, the result of throughput is uncertain. On one hand, a higher power offers a better link quality for a higher rate, which may increase the throughput. On the other hand, a higher power also leads to a longer transmission range, which increases the receiving probability of messages from irrelevant vehicles, and thus the throughput may be decreased. In existing joint adaptation methods, the correlation between two inputs has been explored. But these specific methods cannot extend to more (> 2) inputs. In addition, the theoretical communication model can formulate the correlation if all variables are known. However, some variables cannot be obtained in practical MANETs.

(ii) The correlation is dynamic. The dynamic environment contains a number of uncertainties. For example, field tests in [1] show the highly variable fading phenomenon when vehicles equipped with wireless devices move near I-75, I-275, and I-696 freeway. The reason lies in the complex freeway junction architectures such as a large number of overhead bridges, tunnels, and sudden heavy vehicle traffic. This dynamic environment with uncertainties severely affects the correlation between inputs and outputs as noises. Hence, a conventional static correlation model cannot satisfy the dynamic correlation.

3. Problem model: a control theory perspective

Before introducing the design of JAF, we formulate the wireless system in MANETs as a *Multi-Input Multi-Output* (MIMO) model.

In the wireless system, there are totally i different inputs. For example, $i=2$ inputs include transmission power u_1 and data rate u_2. They are collectively denoted by an input vector $u(k)=[u_1(k)\ u_2(k)]^T$. In this vector, $u(k)$ indicates the input values at the kth time slot. Similarly, the output vector $y(k)=[y_1(k)\ y_2(k)]^T$ is used to describe the $o=2$ outputs, where y_1 is the throughput and y_2 is the PDR. Note that more inputs or outputs can be easily added by appending $u_i(k)$ or $y_o(k)$ into vectors.

The mapping relationship from three inputs to two outputs is described by a general MIMO model according to the adaptive control theory [9]:

$$\begin{aligned} y(k) =& A_1(k)y(k-1)+\cdots+A_n(k)y(k-n)\\ &+B_0(k)u(k-1)+\cdots+B_{n-1}(k)u(k-n)\\ &+e(k), \end{aligned} \tag{1}$$

where $A_j(k)$ and $B_i(k)$ are matrices of model parameters ($A_j\in\mathbb{R}^{o\times o}$, $B_j\in\mathbb{R}^{o\times i}$, and $0<j<n$), n is the order of the model, and $e(k)$ is an identically distributed vector with zero means ($e\in\mathbb{R}^{o\times 1}$). Moreover, e is assumed to be independent with y, u, A and B. We use $e(k)$ to represent the noises.

For simplicity of notation, we rewrite the MIMO model Eq. (1) as:

$$y(k+1)=X(k)\phi(k)+e(k+1), \tag{2}$$

where

$$X(k)=[B_0\ ,\dots,\ B_{n-1}\ A_1\ ,\dots,\ A_n], \tag{3}$$

$$\begin{aligned} \phi(k)=[&u^T(k)\ ,\dots,\ u^T(k-n+1)\\ &y^T(k)\ ,\dots,\ y^T(k-n+1)]^T. \end{aligned} \tag{4}$$

In Eq. (3), the matrix $X(k)$ captures the correlation between inputs as well as their impact on outputs. Leveraging the MIMO model in Eq. (2), we are able to capture both the correlation between three inputs and two performance metrics. As we will show in the following sections, this MIMO model enables a joint control.

4. Design of joint adaptation framework

In this section, we present the design of *joint adaptation framework* (JAF), which jointly controls multiple inputs by exploiting their dynamic correlation in order to achieve the optimal performance.

4.1. Design overview

The architecture of JAF design is depicted in Fig. 2. This design consists of four principal modules:

The *offline estimator* determines the basic structure including the order n and the initial correlation matrix $\hat{X}_{Init}$. Since every wireless device may have different electrical characteristics, it is necessary to estimate the order tailored to every device instead of adopting a unified value. In addition, an accurate estimation of n and $\hat{X}_{Init}$ requires plentiful measurements and long computing time. Hence, we design this offline module.

The *online estimator* learns the real time input-output feedback and updates the estimated correlation $\hat{X}(k)$ in the mobile environment. Compared with the random initial values, the initial $\hat{X}_{Init}$ obtained from the offline estimator can help to approximate the actual correlation $X(k)$ more quickly.

The *adaptive controller* provides the optimal combination of inputs. Using the dynamic correlation, the controller computes the maximal throughput subject to the PDR requirement as an constrained multivariate optimization problem. Furthermore, we plug a smooth mechanism in the adaptive controller in order to avoid the large change of inputs.

The *local measurement* is used to measure the real-time outputs and feed them back to the other modules. With this module, the JAF forms a closed loop system.

The JAF design has three advantages: (i) it explores the implicit correlation between inputs and outputs benefiting from the MIMO model; (ii) it keeps pace with the dynamic environment with uncertainties leveraging the closed-loop control and the online estimator; (iii) this general framework is able to extend to more inputs or outputs. Next, we present the four modules in details.

4.2. Offline estimator design

In order to determine the order n of a MIMO control model, this offline estimator operates as the following steps. Firstly, use the least squares (LS) method to estimate the correlation matrix when setting the order $n=1,2,\dots$, respectively. Secondly, compute the average square error $Z|_n$ for every order n. Thirdly, determine n from $Z|_n$ according to F-criterion or AIC criterion [9]. The offline estimator can be operated by the manufacturer using historical data.

Denote $X|_n$ to be the correlation X when the order of the model is n. Assume that we have L sets of measured inputs $u(k)$ and corresponding outputs $y(k)$, where $k=1,2,\dots,L$ and $L>>n$. According to the formation in Eq. (4), these L measured results can form $(L-n+1)$ different $\phi(k)$, where $k=n,n+1,\dots,L$. Then, $\hat{X}|_n$ can be estimated using LS to approximate the actual X at every n by

$$\hat{X}|_n=Y^T\Phi(\Phi^T\Phi)^{-1}, \tag{5}$$

where

$$Y=[y(n)\ y(n+1)\ \dots\ y(L)]^T, \tag{6}$$

$$\Phi=[\phi(n)\ \phi(n+1)\ \dots\ \phi(L)]^T. \tag{7}$$

The estimation error ε between each pair of measured output and the estimated output is

$$\varepsilon(k)|_n=y(k)-\hat{y}(k)|_n=y(k)-\hat{X}|_n\phi(k-1). \tag{8}$$

Then, the average square error is

$$Z|_n=\frac{\sum_{k=n}^{L}(\varepsilon(k)|_n)^2}{L-n+1}. \tag{9}$$

The order n can be obtained from $Z|_n$ according to the standard F-criterion or AIC criterion, which can be coarsely considered to select the minimal n satisfying $Z'|_n=0$. The order of a wireless system is usually low. The empirical order is 2 obtained from our simulations.

After n is determined, the initial values of correlation $\hat{X}$ are also determined by $\hat{X}_{Init}=\hat{X}|_n$ in Eq. (5).

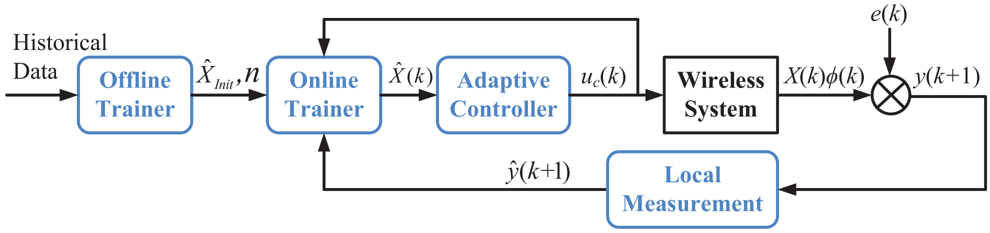

Fig. 2. Architecture of JAF.

4.3. Online estimator design

In a highly mobile environment, the online estimator is required to quickly update the dynamic $X(k)$ at the time slot k. The traditional LS method cannot satisfy the online requirement because it takes a long time to compute the large amount of measurements ϕ. The *recursive least squares* (RLS) method [3] is more suitable, because it is able to update $\hat{X}(k+1)$ with only one measurement $\phi(k)$ and the estimated correlation $\hat{X}(k)$ at last time slot.

Therefore, we adopt the RLS method to update the correlation matrix in this module. Since RLS method has been well studied, we do not repeat the derivation process. Leveraging the method in [3], the dynamic correlation $\hat{X}(k+1)$ can be estimated by the following equations:

$$\hat{X}(k+1) = \hat{X}(k) + \frac{\varepsilon(k+1)\phi^T(k)P(k-1)}{\lambda + \phi^T(k)P(k-1)\phi(k)}, \tag{10}$$

$$\varepsilon(k+1) = y(k+1) - \hat{X}(k)\phi(k), \tag{11}$$

$$P(k) = \frac{P(k-1)}{\lambda} - \frac{P(k-1)\phi(k)\phi^T(k)P(k-1)}{\lambda(1+\phi^T(k)P(k-1)\phi(k))}, \tag{12}$$

where $\hat{X}(k)$ is the estimate of $X(k)$, $\varepsilon(k)$ is the estimation error vector, $P(k)$ is the covariance matrix, and λ is the forgetting factor ($0 < \lambda \leq 1$). A small λ gives exponentially less weight to older measurements and more weight to current measurement, which is helpful in a highly dynamic scenario. The empirical value of this forgetting factor is $\lambda = 0.9$ proposed by [16].

The stability of RLS has been theoretically proved in [3]. We will show the convergence of this design in the evaluation (Section 6).

4.4. Adaptive controller design

The adaptive controller aims to maximize the throughput with the PDR requirement, where the PDR requirement is denoted by R_{req}. Hence, the objective function can be formulated as

$$\begin{aligned} \text{Maximize}:\ & E\{y_1(k+1)\}, \\ \text{Subject to}:\ & E\{y_2(k+1)\} \geqslant R_{req}, \\ & u_1(k) \in U_1, \\ & u_2(k) \in U_2, \end{aligned} \tag{13}$$

where $E\{.\}$ is the expectation operator, U_1 is the set of alternative power levels and U_2 is the set of alternative data rates. The design goal of Eq. (13) can be described as that the expected y_1 is steered to the maximal throughput while subject to several constraints. In particular, the expected PDR must be greater than or equal to the requirement; the transmission power $u_1(k)$ and data rate $u_2(k)$ are limited in their range. For example, $u_1(k)$ is from 0 dBm to 30 dBm in IEEE 802.11p based DSRC.

In accordance with Eq. (11), we have

$$\begin{aligned} E\{y(k+1)\} &= E\{\hat{X}(k)\phi(k) + \varepsilon(k+1)\} \\ &= E\{\hat{y}(k+1)\} + E\{\varepsilon(k+1)\} \\ &= \hat{y}(k+1), \end{aligned} \tag{14}$$

where $\hat{y}(k+1) = \hat{X}(k)\phi(k)$ is the estimate of $y(k+1)$ and the expectation of estimation error is $E\{\varepsilon(k+1)\} = 0$ by RLS theory. Hence, $E\{y_1(k+1)\} = \hat{y}_1(k+1)$ and $E\{y_2(k+1)\} = \hat{y}_2(k+1)$. Then, Eq. (13) can be transformed to

$$\begin{aligned} \text{Maximize}:\ & \hat{y}_1(k+1), \\ \text{Subject to}:\ & \hat{y}_2(k+1) \geqslant R_{req}, \\ & u_1(k) \in U_1, \\ & u_2(k) \in U_2, \\ & \hat{y}(k+1) = \hat{X}(k)\phi(k). \end{aligned} \tag{15}$$

We find that Eq. (15) is a constrained multivariate optimization problem. In addition, each variable $u_1(k)$ or $u_2(k)$ has only finite alternative values, so this function is convex. This typical optimization problem can be easily solved by existing methods such as direct search, gradient-based search, or quadratic programming. For simplicity, we adopt the direct search method to solve this optimization problem Eq. (15) in our design. Then, we obtain the optimal output $y_{opt}(k+1)$ and its corresponding optimal control law $u_{opt}(k)$.

If $u_{opt}(k)$ and $u(k-1)$ are close (*e.g.*, the change of power less than 2 levels), which means the change of input is not large, we set the final control law (*i.e.*, final setting of power and rate) $u^*(k) = u_{opt}(k)$. Otherwise, the smooth control mechanism is triggered, because the severe input oscillation will lead to uncertain impact on other nodes. And the smooth control mechanism can reduce such impact.

The smooth control mechanism aims at minimizing the following quadratic cost function

$$\begin{aligned} J = E\{&||W(y(k+1) - y_{opt}(k+1))||^2 \\ &+ ||Q(u(k) - u(k-1))||^2\}, \end{aligned} \tag{16}$$

where $y_{opt}(k)$ is the optimal outputs obtained from Eq. (15), $||.||$ is the 2-norm operation, W is a positive-semidefinite weighting matrix on the output errors and Q is a positive-definite weighting matrix on the change of input settings. The weighting matrices W and Q are commonly chosen as diagonal matrices. Their relative magnitude provides a way to tradeoff the optimal output for better stability of the input control. Interested readers may refer to [9] for details on W and Q settings.

The design goal of Eq. (16) can be described as that the system outputs approach to the theoretical optimum while penalizing large changes of inputs.

In the following, we derive the smooth control law. First, we define

$$\begin{aligned} \tilde{\phi}(k) = [0\ u^T(k-1)\ ,\dots,\ u^T(k-n+1) \\ y^T(k)\ ,\dots,\ y^T(k-n+1)]. \end{aligned} \tag{17}$$

Substituting $\hat{X}(k)$ and Eq. (17) into Eq. (16), we have

$$\begin{aligned} J &= E\{||W(\hat{X}(k)\tilde{\phi}(k)+\hat{B}_0 u(k)+\varepsilon(k+1)) \\ &\quad -y_{opt}(k+1))||^2\}+||Q(u(k)-u(k-1))||^2 \\ &= ||W(\hat{X}(k)\tilde{\phi}(k)-y_{opt}(k+1))||^2+||W\hat{B}_0 u(k)||^2 \\ &\quad +2u^T(k)\hat{B}_0^T W^T W(\hat{X}(k)\tilde{\phi}(k)-y_{opt}(k+1)) \\ &\quad +||Qu(k)||^2+||Qu(k-1)||^2 \\ &\quad -2u^T(k-1)Q^T Qu(k)+E||W\varepsilon(k+1)||^2. \end{aligned} \tag{18}$$

The cost function J is at its minimum where the following derivative is zero.

$$\begin{aligned} \frac{\partial J}{\partial u(k)} &= 2(W\hat{B}_0)^T W(\hat{X}(k)\tilde{\phi}(k)-y_{opt}(k+1)) \\ &\quad +2(W\hat{B}_0)^T W\hat{B}_0 u(k) \\ &\quad +2Q^T Qu(k)-2Q^T Qu(k-1) \\ &= 0. \end{aligned} \tag{19}$$

Solving Eq. (19), we obtain the smooth control law $u_{smo}(k)$

$$\begin{aligned} u_{smo}(k) &= \left((W\hat{B}_0)^T W\hat{B}_0+Q^T Q\right)^{-1}\cdot\left(Q^T Qu(k-1)\right. \\ &\quad \left.+(W\hat{B}_0)^T W(y_{opt}(k+1)-\hat{X}(k)\tilde{\phi}(k))\right) \end{aligned} \tag{20}$$

as the final control law $u^*(k)=u_{smo}(k)$. Note that the smooth control mechanism does not violate the convergence to the optimal output, but consume a longer convergence duration in exchange for a more smooth change of inputs.

4.5. Local measurement design

It is non-trivial to acquire other nodes' throughput and PDR because of the hybrid communication manner. In this module, the measurements are defined for unicast and broadcast, respectively. For the unicast manner, the values of both throughput and PDR can be attached in the acknowledgement (ACK). Hence, a node could acquire its neighbors' performance directly from the ACK. On the contrary, for the broadcast manner, there is no ACK mechanism. This module measure $y(k)$ by the average performance of all neighbors. Based on the channel reciprocity, neighbors can have similar transmission performance because every node operates the same JAF. Thus, the core idea of local measurement is to utilize a node's own performance $\hat{y}(k)$ to approximate the average performance of its neighbors $y(k)$. Note that a node can measure its performance including throughput and PDR locally.

5. JAF analysis

In this section, we analyze the compatibility, complexity, and stability of JAF design.

5.1. Compatibility analysis

The operation of JAF needs the throughput and PDR measurements, which are computed using the physical layer information. Moreover, the transmission power and data rate are also physical or MAC layer variables. Hence, JAF should be placed close to the physical layer. Meanwhile, the position of JAF should be higher than lower MAC layer because the data rate must be determined before adding it into the header of MAC frame. Using 802.11p based DSRC as an example, we set JAF as a middle MAC layer between the upper MAC layer of IEEE 1609.4 and the lower MAC layer, which can merge into the existing DSRC protocol stack as shown in Fig. 3. In this way, the function of JAF can be enabled and disabled on demand. And it does not conflict with any other layers. In addition, JAF does not require any change of existing protocol stack, which shows it strong compatibility.

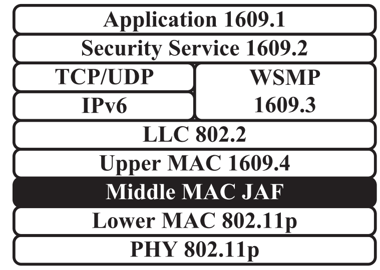

Fig. 3. JAF is designed as a middle MAC merged into current existing wireless protocol stack. For example, in DSRC.

5.2. Time cost analysis

In JAF, there are two online modules, the online estimator and the adaptive controller, involve in the computing tasks. For practice, the time cost of these two modules are desired to be low. Otherwise, a large time cost will decrease the throughput.

With respect to the online estimator, the main task of RLS is to solve $\hat{X}(k+1)$ in Eq. (10), whose complexity is owing to the matrix multiplication. According to [8], the complexity of $P(k)$ is determined by $P(k-1)\phi(k)\phi^T(k)P(k-1)$, where the size of $P(k-1)$ is $(i+o)n\times(i+o)n$ and $\phi(k)$ is $(i+o)n\times 1$. Thus, $P(k)$ is $\mathcal{O}((i+o)^4n^4)$; Similarly, the complexity of $\varepsilon(k+1)$ is $\mathcal{O}(o(i+o)^2n^2)$; And the final complexity of the online estimator for $\hat{X}(k+1)$ is $\mathcal{O}(o(i+o)^7n^7)$ determined by $\varepsilon(k+1)\phi^T(k)P(k-1)$. Since all parameters $o=2$, $i=2$, and $n=2$ are very small, the time cost of the online estimator is low.

In regard to the adaptive controller, the main task is to obtain the control law u^* according to Eq. (15). Even using the inefficient direct search method, the computational complexity is $\mathcal{O}(\varrho_1\varrho_2\varrho_3 o(i+o)^2n^2)$, where ϱ_1, ϱ_2, and ϱ_3 are the number of alternative power levels and data rates, respectively. In detail, the search space is $\varrho_1\varrho_2\varrho_3$ including all combinations of three inputs. And for each combination, $\hat{y}(k+1)=\hat{X}(k)\phi(k)$ needs to be computed, whose complexity is $\mathcal{O}(o(i+o)^2n^2)$. *e.g.*, in DSRC, $\varrho_1=32$, $\varrho_2=8$ and $\varrho_3=9$, the time cost of adaptive controller is also low.

5.3. Stability analysis

The main components involved in stability of JAF include the MIMO model and the adaptive controller. (i) In this work, we approximate the wireless system in MANET as a linear MIMO model. (ii) The adaptive controller is a constrained multivariate optimization function, in which one output y_1 is set as the optimization objective and another output y_2 is set as the constraint. So the optimal outputs can always be derived. Hence, JAF is a stable control strategy. In addition, we evaluate the stability in simulations.

6. Performance evaluation

To evaluate JAF in MANETs, we implement it on the ns-2 simulation platform and perform extensive simulations in a vehicular network, which is a typical MANET application.

6.1. Simulation settings

The simulation settings are as follows:

Highway Scenario. We conduct our simulations in a typical bi-directional highway scenario. The bi-directional highway is of 2000 meters long and 30 meters wide with four lanes in each direction. In addition, there are two entries along each direction. One entrance is at the beginning of the highway, and the other is at the 1-kilometer spot on the highway. Vehicles randomly enter the

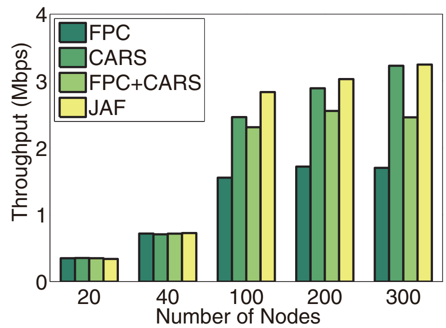

Fig. 4. Average throughput under different traffic densities.

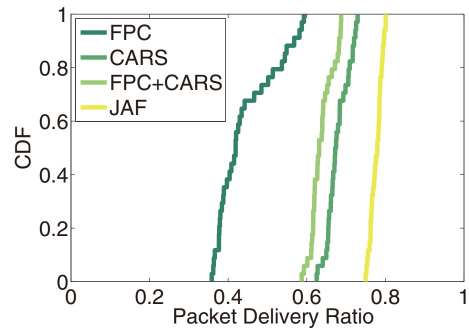

Fig. 5. The CDF of average PDR when the node number is 100.

highway through all four entries and drive with a speed limit of 100 kms per h. Upon arriving at the end of one direction, vehicles go off the highway and enter the highway again at the other direction. The total number of vehicles varies from 20 to 300. The traffic traces are generated by SUMO, which provides microscopic movement logs of vehicles.

Vehicle Settings. Each vehicle is considered as a mobile node and is equipped with a DSRC radio. For each node, the default transmission data rate is set as 3 Mbps for maximizing the packet delivery ratio. The other options of data rates are 6 Mbps, 12 Mbps and 24 Mbps. The default transmission power is set to 20 dBm. Each vehicle can adjust its transmission power from 0 dBm to 30 dBm with a 2 dBm step.

Communication Settings. Each node can either unicast or broadcast its messages. The generation periods of unicast messages and broadcast messages are 0.1 s and 1 s, respectively. If a unicast message is generated, a node will randomly selects a neighboring node to transmit this message. The packet size is set to 500 bytes, which is a typical packet size used in industrial projects (e.g., California Department of Transportation/Air Resources Board Modeling Program).

Propagation Model. We employ the V2V channel model [6] in our ns-2 simulation platform. This model is established through field tests. It uses a two-slope function to capture the propagation features of a vehicular scenario.

Methods Studied. We comparatively study the following adaptation methods in our simulations:

- JAF: the joint adaptation framework we propose in this paper. It jointly controls the transmission power and data rate according to the local measurements of the throughput, PDR and environment parameters.
- CARS [21]: a state-of-the-art data rate adaptation method tailored for vehicular networks. In our evaluation, CARS exploits environment measurements including the SINR value, velocity, and density to select the optimal data rate.
- FPC [10]: a feedback-based transmission power control method. FPC aims to control the transmission range of each vehicle at a proper value. To achieve this, FPC utilizes the feedback beacons in broadcast packets as transmission power control references.
- FPC+CARS: a sequential combination of FPC and CARS. It first adjusts the transmission power based on FPC, then chooses the data rate using CARS.

6.2. Performance results of throughput and PDR

Fig. 4 shows how the throughput changes with the traffic density. As we can observe from the figure, the throughput first increases with the traffic density and then reaches a saturated value. This is because as more and more nodes appear in the communication range of a node, the amount of received packets start to increase. However, there is an upper limit of throughput due to the wireless collision. The results show that JAF can adapt to a changing environment much better than existing solutions. Compared to CARS and FPC, JAF can significantly increase the throughput via applying joint control of all variables. In Fig. 4, it is also worth noting that FPC+CARS yields a lower throughput than CARS. This result indicates that a poor design of sequential control for several variables one-by-one would obtain a worse performance than just one variable adaptation. This result further demonstrates that multiple variables are not independent from each other. Therefore, there exists a tradeoff between multiple variable. FPC+CARS ignores such a tradeoff, and even decreases the wireless performance with an inappropriate combination of transmission power and data rate. In contrast, JAF utilizes a MIMO model, which implicitly correlates all variables. Hence, JAF is able to provide a better combination than that of FPC+CARS and CARS.

Fig. 5 shows the cumulative distribution function (CDF) of each node's average PDR, when the number of nodes is 100. In this case, the wireless channel is approaching the saturation point. It is shown in Fig. 5 that JAF achieves the highest PDR. Compared with the second best method, JAF increases the worst-case PDR by up to 15.2% (The corresponding improvement in throughput is 13.1%.). Considering the congested and nearly saturated channel, this improvement is considerable. In Fig. 5 we can also find that FPC (which fixes its data rate as 3Mbps) yields the lowest PDR. This suggests that the 3 Mbps data rate is not always the most reliable data rate. On the contrary, JAF and CARS adjust the data rates once the channel becomes too congested for the data rate of 3 Mbps. As a result, JAF and CARS outperforms FPC when the traffic density is large.

6.3. Selection of transmission power and data rate

Then, we illustrate the insights of JAF by comparing the selections of data rate and transmission power of different methods. Without loss of generality, we randomly choose a scenario, in which the number of nodes is 100.

Fig. 6 presents the occurrence probability of each data rate, and Fig. 7 summarizes the occurrence probability of each transmission power. In this case, the channel is approaching a congested state. To deal with this congested channel and reduce the collision probability, both JAF and CARS intend to use the data rate of 12 Mbps as shown in Fig. 6. CARS uses 12 Mbps in 77.0% of the cases. However, it cannot further improve the performance, as the SINR value cannot be further increased without transmission power control. Due to the limited SINR, CARS falls back to 3 Mbps and 6 Mbps in 23% of the cases. Combining the finding that FPC+CARS performs even worse than CARS as shown in Figs. 4 and 5, these observations further verify that an inappropriate joint control sometimes harms the performance. In order to better support the data rate of

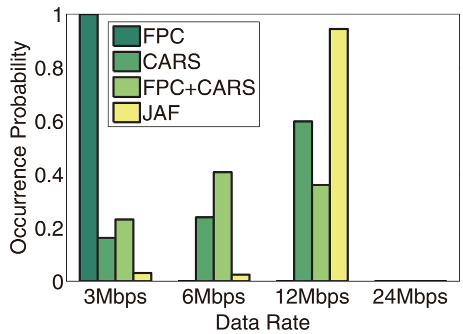

Fig. 6. The occurrence probability of each data rate.

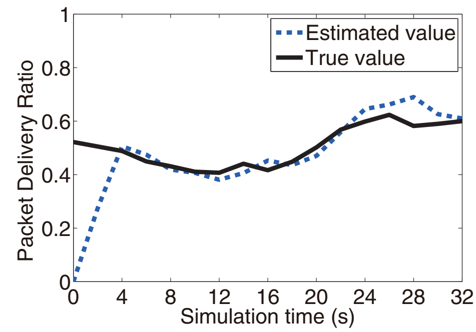

Fig. 9. The convergence of the estimated PDR.

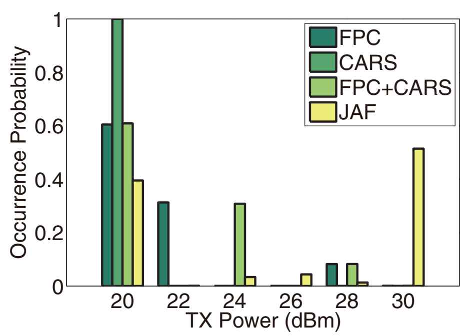

Fig. 7. The occurrence probability of each transmission power.

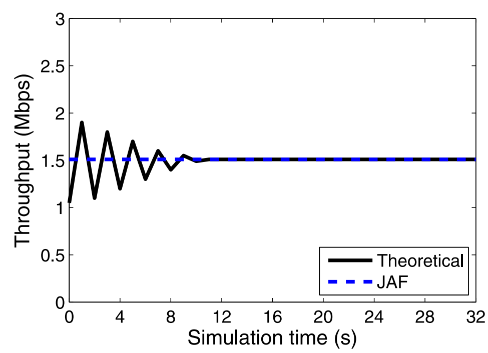

Fig. 10. The stability of JAF.

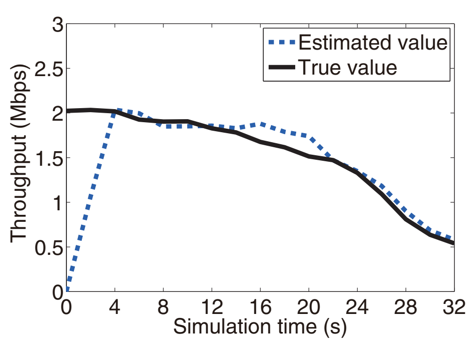

Fig. 8. The convergence of the estimated throughput.

12 Mbps, JAF employs high transmission powers more frequently than other methods as shown in Fig. 7. It applies the highest transmission power 30 dBm in 51.4% of all the cases. Higher transmission powers allow JAF to increase the SINR of the receivers. Consequently, JAF is able to use the data rate of 12 Mbps in 94.4% of the cases and fully exploit the advantage of this data rate. This result suggests that a good combination enables JAF to further improve the wireless performance in MANETs.

6.4. Convergence of the online estimator

We also evaluate the convergence of the online estimator of JAF. Traffic conditions of individual nodes in the same MANET are different. For each one, its traffic condition also varies from time to time. We randomly pick a node, and investigate the convergence of its online estimator. Fig. 8 presents the estimated and actual values of throughput. It shows that the estimation provided by the online estimator can quickly converge to the actual value in only 2 update periods. After that, the estimated value follows the change of the actual value closely. We also have similar observations on the estimation of PDR as shown in Fig. 9. Therefore, we conclude that the online estimator of JAF converges quickly.

6.5. Stability of JAF

Stability is an important metric in control systems. To verify the stability, we conduct a simulation that all nodes are randomly distributed and stationary in the area. In mobile scenario, since inputs keep changing according to the dynamics, the stability cannot be recognized clearly. Thus, we simulate in such a stationary scenario, which is a general snapshot of mobile scenario. The change of throughput of one certain node is plotted in Fig. 10. We can summarize that JAF is stable, which reaches a constant output after 10s and is overlapped with the theoretical result.

7. Related work

Adaptation methods have been extensively studied in wireless communications. In this section, we only discuss the work that is most pertinent to ours.

In stationary wireless networks, the classical power control method PCMAP [18] samples several successive SNR values for optimal power estimation. Similarly, the classical rate selection methods ARF [15], SampleRate [2], and RRAA [24] decide their optimal data rates in a given time window by measuring the number of successive packet losses, the average of per-packet transmission times, and the packet loss ratio, respectively. All these methods operate based on a long window to sample measurements. Therefore, they can work well in relative stationary networks, but cannot keep pace with the quick changes in highly dynamic MANETs.

In mobile networks, most adaptation methods take the mobility into account. For example, LINT [19] adjusts the power for topology control in mobile networks using the dynamic number of neighbors. RBAR [13] selects the optimal rate by the receiver-based SNR measurements. Then, RAM [5] extends the receiver-based rate adaptation design with channel asymmetry in consideration. SoftRate [23] determines the best rate using the channel bit error rate, which is estimated by the physical layer information. D-FPAV [22] focuses on the transmission fairness of safety-critical information by a distributed power control method. FPC [10] utilizes feedback beacons to adapt the power level to a proper transmission range. CARS [21] is a customized rate selection method for VANETs, which leverages context information such as velocity and distance to perform fast rate adaptation. DORA [4] works under the noisy VANET channels for optimal rate selection. Nevertheless, these methods only focus on single variable's adaptation, which totally ignore the impact of multiple inputs and multiple outputs. Thus, they cannot attain the optimum in our problem.

Only a few VANET works pay attention to joint control. For example, Huang et al. [14] proposes the joint transmission probability and power control for accurate tracking. Rawat et al. [20] studies the joint power and contention window size control for dissemination performance. The joint control methods in these papers are sequential combinations of multiple individual control methods. Therefore, they fail to capture the correlation between variables, and can only achieve suboptimal performance and reliability.

8. Conclusion

In MANETs, not only single variables but also their correlation significantly affect the performance of wireless communications. To enhance the performance, we present a general adaptation framework JAF, which considers the wireless system as an MIMO control model. Based on the MIMO model, JAF captures the dynamic correlation between multiple inputs and outputs using an online estimator. Leveraging the estimated correlation, JAF then jointly adjusts the inputs to achieve the optimal outputs. Extensive simulation results demonstrate that JAF significantly outperforms the state-of-the-art adaptation methods and their combination.

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